

Adaptive Localization Algorithm for Movement of Mobile Node

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Abstract— Existing localization algorithms which use Kalman filter for indoor environment fix noise covariance or change noise covariance by complicated filters. Since localization system does not reflect real environment around it, fixed noise covariance makes localization system unpractical. Also complicated filters limit the applications which localization algorithms can apply. In this paper, we propose a method that adaptively changes noise covariance. The proposed method recognizes changes of moving pattern based on results of localization, and then adjusts the noise covariance. In addition, the method varies localization period to catch up with changed mobile nodes's movement rapidly and reduce overhead caused by calculation of location when mobile node moves regular pattern. Simulation result from MATLAB shows the proposed method outperformed an algorithm which has constant localization period and noise covariance of Kalman filter by 30%.

Keywords—Kalman filter, Localization, indoor, Mobile node

I. INTRODUCTION

Since a requirement of Emergency - 911 by FCC, cell phone service providers have been demanded to provide a localization service. Therefore, researches about localization have processed actively. Wireless localization can be categorized an indoor localization and an outdoor localization. GPS and cellular network are used for an outdoor localization. RFID, WLAN and UWB are studied as an indoor localization. Accuracy of indoor localization is affected by non line of sight and multi-path propagation. P. Krishnamurthy et al. exploit a statistical database to increase localization accuracy [2], [3]. This method uses database of propagation delay and attenuation in a region where localization system will be installed. On the other hand, Bao Long Le et al. improved localization accuracy by adopting Kalman filter which has a noise cancelling property [4], [5]. It means Kalman filter compensates for localization error by weighting adaptively between a measured location and a predicted location from previous state and error information. Jeon et al. introduced a method that uses above two methods [6], statistical database and Kalman filter. When the Kalman filter is used as a way of improving localization performance,

it is important that the Kalman filter selects an optimal Kalman gain. The Kalman gain is a critical factor when the algorithm calculates each weight about predicted location and measured location. The Kalman gain is related to noise covariance. Existing algorithms for localization using Kalman filter fix noise covariances, or change noise covariances using other complicated filters. If the noise covariances are fixed, it can not reflect practical environment. Therefore, the Kalman gain is not optimal, and this brings a decrease of localization accuracy. Instead, if a localization algorithm uses a complicated filter to change the noise covariances, it will increase localization accuracy, but it also increases complexity of the algorithm. In this paper, we propose a method which recognizes changes of mobile node's moving pattern and adjusts noise covariance and localization period to fit into newly changed moving pattern. This method does not need an additional device, such as accelerometer, inertial sensor, or complicated filter to detect changes of mobile node's moving pattern. It only uses measured localization data. In addition, our method reduces localization overhead by adaptively regulating localization period based on movement of mobile node. Simulation result shows that our method outperformed an algorithm which has constant localization period and noise covariance by 20% of error reduction. The rest of this paper is organized as follows. In Section 2, we survey related work in Kalman filter and existing localization algorithms using Kalman filter. In Section 3, we describe our proposed method in detail. Section 4 includes simulation result to verify performance of our method. Finally, we present conclusion in Section 5.

II. RELATED WORK

A. Kalman Filter

Kalman filter is a recursive estimator. It means that present state is calculated with present measured value and previous state. It does not need a measurement history, and it has outstanding noise cancelling property. Hence, it is usually applied to a tracking algorithm of flights or rockets. The Kalman filter can divide two processes, the Predict process and Update process. In the Predict process, the Kalman filter predicts a present states from previous state and process noise information as follows (1),(2).

$$x_k^- = Fx_{k-1} + Bu_{k-1} \quad (1)$$

$$P_k^- = FP_{k-1}F^T + Q \quad (2)$$

In update process, it determines a present state by applying Kalman gain (K) to a measured value and a predicted value which is calculated in Predict process.

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \quad (3)$$

$$x_k = x_k^- + K_k(z_k - Hx_k^-) \quad (4)$$

$$P_k = (I - K_k H)P_k^- \quad (5)$$

From above equations, x is a state variable that we want to optimize, and F is a state transition coefficient. B and u are inputs of the system. Q is a process noise expressed as a covariance. Z is an measured value. R is a measurement noise, and it is used as a covariance matrix form in the above equation. Actually, the process noise and measurement noise are not constant, but varying along with time. Therefore, it is hard to applicable precisely to Kalman filter. In many algorithms using Kalman filter, a measurement noise covariance is calculated from samples which surveyed in advance, and this covariance(R) is used as a measurement noise information. Besides, process noise information is found by heuristic method, or already known when the system was made.

B. Localization using Kalman Filter

Figure 1 shows a localization system which exploits the Kalman filter. Mobile node executes ranging process, and measures distances between mobile node and at least three anchor nodes. After that, coordinates of each anchor node and measured distance information are inputted to Least Square Estimator(LSE) to calculate a present location. In this process, LSE calculates a mobile node's location which might be minimal from each anchor node's distance error. Next, the Kalman filter corrects a coordinate by considering a predicted coordinate. This process is presented in (4). The correction is done by weighting differently on predicted coordinate and measured coordinate. As shown above equations, the Kalman gain(K) is a weighting factor that consists of process noise covariance(Q) and measurement noise covariance(R). If a value of Q decreases, K will reduce. That means the confidence of a predicted coordinate is higher. Besides, when R decreases, K will increase, so it trusts a measured coordinate better than the predicted. Existing many localization systems using Kalman filter fix these covariance[6], or use complicated algorithm to change these values adaptively. Hence, the localization change these

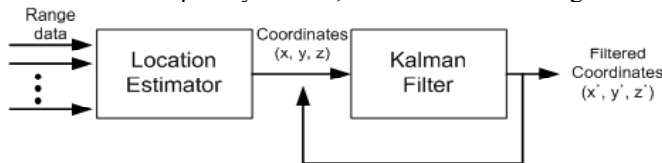


Figure 1. An architecture of allLocalization algorithm which uses the Kalman filter

values adaptively. Hence, the localization accuracy decreases, or the complexity of system and processing burden increase, so it limits applications whose localization algorithm can apply to.

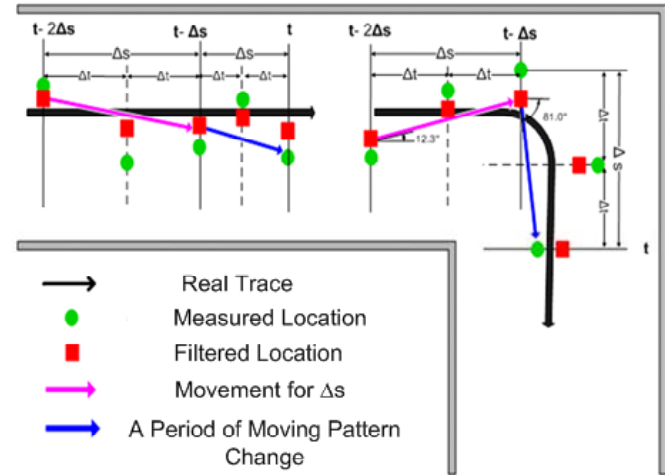


Figure 2. The method to recognize a change of speed or direction

III. MOVEMENT ADAPTIVE LOCALIZATION ALGORITHM

This section illustrates the proposed localization algorithm in detail. The proposed method changes the noise covariance and localization period according to changes of moving direction or speed of target. It increases accuracy of localization and decreases calculation burden.

A. Important Parameter

Important parameters in the proposed algorithm are explained below.

- Localization Period (LP, Δt): LP means a time interval between two consecutive localizations. In this period, a mobile node ranges with more than three anchor nodes then calculates a location.
- Moving Pattern Measurement Period MPMP, Δs): During this period, we can make a decision of moving pattern of mobile node. Speed and direction of mobile node are calculated in each this period, and then they are compared with previous period results to determine a change of moving pattern.

B. A method of recognition about moving pattern change

A recognition method of moving pattern change can divide into speed change recognition and direction change recognition. A velocity change is recognized by comparing each moving distance of two consecutive MPMP. If the difference of two moving distance is larger than a threshold which related to moving distance, the algorithm determines a change of speed. In the same way, a moving direction change is determined by calculating a difference of each moving direction of two consecutive MPMP and compares with its threshold which selected in advance. If the difference is larger than threshold, it assumes the change of moving direction. Figure 2 shows the manner of moving pattern change recognition. In this figure, MPMP(Δs) is chosen two fold of LP(Δt). First, the algorithm calculates moving distance and direction between $t - \Delta s$ and t .

Then, it calculates same variables from $t-2\Delta s$ to $t-\Delta s$. After that, it calculates differences between each same type variable. If these differences are larger than each threshold, the algorithm concludes a change of moving pattern.

C. Movement adaptive localization algorithm

The proposed algorithm senses a change of mobile node's moving pattern and adaptively adjusts the $LP(\Delta t)$ and noise covariance of Kalman filter. A specific algorithm is illustrated below.

1) In each localization period, a mobile node ranges with more than three anchor nodes, and then these data are used to calculate a coordinate in the Least Square Estimator.

2) The difference between two coordinates, one is outputted from Least Square Estimator and other coordinate is determined before Δs , is calculated on cartesian coordinate system. In the same way, the difference between coordinates before Δs and $2\Delta s$ is calculated on Cartesian coordinate system. A difference of two results obtained previously is expressed by cylindrical coordinate system.

$$\sigma_t = \sqrt{(x_{\Delta s} - x_{2\Delta s})^2 - (y_{\Delta s} - y_{2\Delta s})^2} \quad (6)$$

$$\phi_t = \arctan((y_{\Delta s} - y_{2\Delta s}) / (x_{\Delta s} - x_{2\Delta s})) \quad (7)$$

We assume two dimensions. The first coordinate(σ) means change of speed and a second coordinate(ϕ) shows direction alteration in the cylindrical coordinate system.

3) The calculated σ_t and ϕ_t are compared to each threshold. The thresholds are set before starting system and should be set larger than maximum error that can be experienced.

4) If σ_t is over than Threshold σ , it decreases the $LP(\Delta t)$. Otherwise, if σ_t is smaller than Threshold σ , it increases the $LP(\Delta t)$. If ϕ_t is larger than Threshold ϕ , it decreases a localization period and adjusts a noise covariance for placing more weight to a measurement coordinate. If ϕ_t is smaller than Threshold ϕ , the algorithm increases a localization period and adjusts a noise covariance to place more weight on a predicted coordinate in filtering process.

IV. PERFORMANCE EVALUATION

In this section, we will show performance evaluation of proposed algorithm. It is evaluated by MATLAB simulation, and it is compared with a localization algorithm which has constant localization period and noise covariance.

A. Simulation environment

For simulation, four anchor nodes are installed at each corner in 10 meters of square area. A mobile node localizes continuously while it moves like Figure 3. We used two scenarios. The first scenario is Figure 3 left, a mobile node moves along the x axis for the first fifteen seconds, after that it went along y axis during next fifteen seconds. This move-

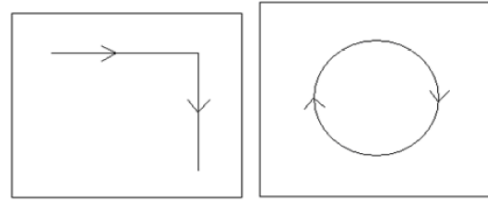


Figure 3. Mobile node's moving scenario 1(left) and scenario 2(right)

ment is often happened when a person walk on the hallway or enter a room. In this scenario, a mobile node maintained 0.6m/s of speed. This is normal walking speed of person. In the second scenario, a mobile node turned around with 0.75m/s for 30 seconds like Figure 3 right. This scenario is selected to simulate a case when the mobile node changes a moving pattern continuously.

Table 1. Experiment Result of Indoor Ranging with NANOTRON Board

Real distance	Average	Standard deviation	Distance error
1m	1.60m	0.16m	0.60m
2m	2.95m	0.14m	0.95m
3m	4.36m	0.17m	1.36m
4m	5.65m	0.17m	1.64m
5m	6.41m	0.13m	1.41m
6m	6.74m	0.13m	0.74m
7m	7.88m	0.18m	0.88m

In advance of simulation, we did a ranging experiment to model the ranging error with NANOTRON boards in line of sight environment. NANOTRON board uses Chirp signal and SDS-TWR[9] method to check a distance between two nodes. Table I is a result of experiment, and it is reflected in ranging model(8). Thus we assume that ranging error of mobile node has Gaussian distribution with 0 mean value and 0.162m of standard deviation.

$$\text{Measured range} = \text{True range} + N(0, 0.162) \quad (8)$$

When we simulate, the process noise covariance and localization period is acquired by heuristic method. Process noise covariance is used 0.01 or 1. If the algorithm wants more weight to a predicted coordinate, it selects 0.01. Otherwise, it selects 1. Localization period is chosen default, minimum, maximum value as 0.2, 0.1, 1 second respectively. Also, when the localization period is adjusted, it is doubled or halved between 0.01 and 1. To evaluate performance of our algorithm, we used Root Mean Squared Error(RMSE).

$$\text{Root Mean Squared Error} = \sqrt{\frac{\sum (\text{True position} - \text{Estimated position})^2}{n}} \quad (9)$$

B. Simulation result

Figure 4 and 5 are result of the first scenario. The proposed algorithm and contrast algorithm which uses Kalman filter with constant noise covariance and localization period had the similar number of localization times. The RMSE after Kaman filter decreased 4.8% comparing to RMSE after LSE in the contrast algorithm. By comparison, proposed algorithm shows that the coordinates after Kalman filter was reduced 39% of error comparing to unfiltered coordinates. This result has two

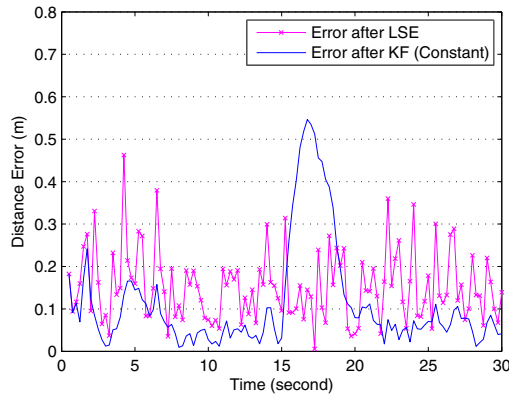


Figure 4. Distance error of localization algorithm using constant noise covariance of Kalman filter and fixed localization period on scenario 1

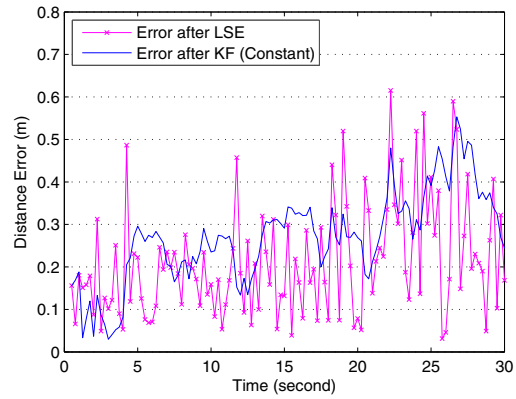


Figure 6. Distance error of localization algorithm using constant noise covariance of Kalman filter and fixed localization period on scenario 2

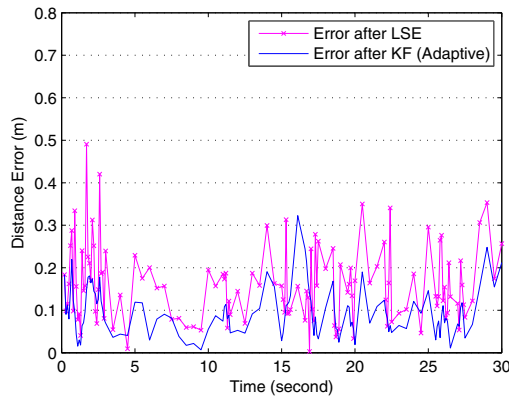


Figure 5. Distance error of proposed localization algorithm on scenario 1

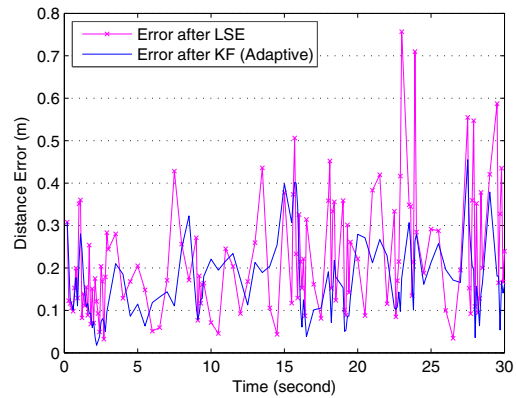


Figure 7. Distance error of proposed localization algorithm on scenario 2

Table 2. Simulation Result for scenario 1

	RMSE after LSE	RMSE after KF	Improvement
Figure 4	0.1757m	0.1671m	4.8%
Figure 5	0.1819m	0.1105m	39.2%

main reasons. After starting algorithm, there is no previous data. Hence, the contrast algorithm takes few seconds to be stable and during that time localization have large error. However, our algorithm shortened this time by adaptively controlling localization period and noise covariance. When a mobile node changes its direction at 15 seconds, our method sensed a moving pattern change and adaptively adjusted localization period and noise covariance. We can see that our algorithm caught up well with real movement around 15 seconds, but contrast algorithms took a time to fit with real movement. Consequently, Figure 5 comparing to Figure 4 can see that our method's trace is similar to scenario's at the point of initial and changing direction.

Figure 6 and 7 are results about the second scenario. Contrast algorithm shows -5.1% improvement of RMSE between coordinates before and after Kalman filter and our method reduced 27.9% RMSE. In second scenario, we also could get better performance than the contrast algorithm because proposed method flexibly changes a noise covarian-

Table 3. Simulation Result for scenario 2

	RMSE after LSE	RMSE after KF	Improvement
Figure 6	0.2636m	0.2771m	-5.1%
Figure 7	0.2625m	0.1891m	27.9%

ce and localization period by sensing the variation of moving pattern

Figure 8 shows graphs that RMSE of 500 times simulation on each scenario is averaged. The contrast algorithm had 8% RMSE reduction comparing coordinates passed Kalman filter to coordinates before the Kalman filter in the first scenario. Our algorithm improved 40% RMSE between coordinates after and before Kalman filter. Accordingly, our algorithm outperformed contrast algorithm by 30% RMSE decrease. Similarly, filtered coordinates of contrast algorithm had 4% RMSE decrease than coordinates before filtering in the second scenario, and in case of proposed algorithm, filtered coordinate decreased 34% RMSE comparing to coordinates ahead of Kalman filter. Namely, our method reduced 30% more RMSE than the contrast algorithm.

V. CONCLUSIONS

In this paper, we proposed an algorithm that senses a moving pattern change, and it adjusts noise covariance and localization period adaptively. The simulation results show 30%

performance improvement comparing our method to the contrast algorithm. To acquire similar performance like our algorithm with contrast algorithm, it needs shorter localization period about $1/2 \sim 1/3$ than constant period used.

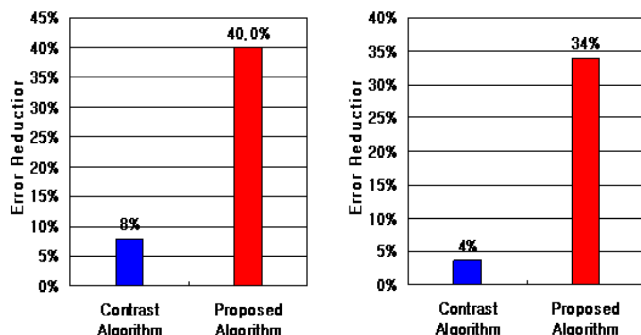


Figure 8. Performance comparison on scenario 1(left) and scenario 2 (right)

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